Chapter 5
Pattern Recognition of Handwritten English Characters

ABSTRACT

After success of a total solution to handwriting 99 multiplication by deep learning, this chapter further addresses on the problem with increased complexity. In addition to handwritten digital dataset, the EMNIST database provides multiple balanced or unbalanced datasets. These datasets contain different combinations of handwritten digit and letter images. It is believed that well trained deep CNNs can handle unbalanced datasets, so this chapter chose By_Class of EMNIST database as a dataset to increase the difficulty of problem solving and extend the application of iOS Apps. This chapter discusses classification of handwritten English character, including uppercase and lowercase, data audition due to requirement of further improvement, and online tests on iOS devices. After a long time of training, the developer got the pre-trained CNN model. For 58,405 testing images, the recognition accuracy rate was as high as 97.0%.

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AUDITED DATASET OF HANDWRITTEN ENGLISH LETTERS

After the appearance of the CNN model, the pattern recognition of handwritten characters seems basic and simple. But it is more difficult than imagined actually. Different from printed characters, handwritten characters may be irregular, sloped, and distorted. As a human being, to distinguish others' handwritten characters is also not simple. After solving the recognition problem of handwritten digits, we believe that the recognition of handwritten letters will be another valuable topic for research. In present, there are many consumer electronics with touch-screen surrounding, such as smartphone, iPad, computer, GPS, camera and so on. The touch-screen not only retains the function of display but also replaces physical type-in buttons. We can watch videos, draw pictures, type, command transmission and so on via touch-screen. We used to store information on paper, but now we tend to store electronically in the hard disk or cell phone. The developed recognition model of handwritten letters can efficiently convert handwritten characters on photos or touch-screens into electronic characters and store them. We can import the recognition model of handwritten letters to iOS devices and realize practical applications, such as handwriting crossword puzzles, handwriting notepads, handwriting translator and so on. If the recognition model of handwritten letters combines with handwritten digits in Chapter 4, we can also import to traffic enforcement cameras to detect the license plate of the speeding vehicle. Obviously, the recognition model of handwritten letters could be widely applied in real life.

In Chapter 4, handwriting 99 multiplication employs off-line handwritten digit recognition. Relative to on-line character recognition, off-line handprinted character recognition possesses more extensible applications to iOS pattern recognition App design. The App design in this chapter adopts off-line handwritten English character recognition (Grother P. J., 1995) (Grother & Hanaoka, 2016) (Netzer, et al., 2011) (Grother & Hanaoka, 2016) which is feasible for handprinted document recognition (LeCun, Bottou, Bengio, & Haffner, 1998) (Netzer, et al., 2011) (Radtke, Sabourin, & Wong, 2008).

NIPS special database 19 was released in 1995 (Grother P. J., 1995) for automatic handprinted document and character recognition. The original version of NIPS special database 19 contains 3669 handprinted documents

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